

Beyond Sentiment: The Manifold of Human Emotions

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Abstract

Sentiment analysis predicts the presence of positive or negative emotions in a text document. In this paper we consider higher dimensional extensions of the sentiment concept, which represent a richer set of human emotions. Our approach goes beyond previous work in that our model contains a continuous manifold rather than a finite set of human emotions. We investigate the resulting model, compare it to psychological observations, and explore its predictive capabilities. Besides obtaining significant improvements over a baseline without manifold, we are also able to visualize different notions of *positive sentiment* in different domains.

1 Introduction

Sentiment analysis predicts the presence of a positive or negative emotion y in a text document x . Despite its successes in industry, sentiment analysis is limited as it flattens the structure of human emotions into a single dimension. “Negative” emotions such as depressed, sad, and worried are mapped to the negative part of the real line. “Positive” emotions such as happy, excited, and hopeful are mapped to the positive part of the real line. Other emotions like curious, thoughtful, and tired are mapped to scalars near 0 or are otherwise ignored. The resulting one dimensional line loses much of the complex structure of human emotions.

An alternative that has attracted a few researchers in recent years is to construct a finite collection of emotions and fit a predictive model for each emotion $\{p(y_i|x), i = 1, \dots, C\}$. A multi-label variation that allows a document to reflect more than a single emotion uses a single model $p(y|x)$ where $y \in \{0, 1\}^C$ is a binary vector corresponding to presence or absence of emotions. In contrast to sentiment analysis, this approach models the higher order structure of human emotions.

There are several significant difficulties with the above approach. First, it is hard to capture a complex statistical relationship between a large number of binary variables (representing emotions) and a high dimensional vector (representing the document). It is also hard to imagine a reliable procedure for compiling a finite list of all possible human emotions. Finally, it is not clear how to use documents expressing a certain emotion, for example tired, in fitting a model for predicting a similar mood, for example sleepy. Using labeled documents only in fitting models predicting their denoted labels ignores the relationship among emotions and is problematic for emotions without many annotated documents.

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We propose in this paper a different approach for modeling the human emotions that are expressed in text documents. Our approach is motivated by two observations: (a) human emotions are arranged on a low dimensional manifold, and (b) it is easier to construct statistical models for low dimensional continuous data than for high dimensional discrete data.

Specifically, we consider a joint distribution over three random objects X, Y, Z where X is a document, Y is a categorical variable representing the emotion reflected in X , and Z is the corresponding location on the manifold of emotions. We posit the statistical relationship $X \rightarrow Z \rightarrow Y$, implying that Y is conditionally independent of X given Z . In other words, the manifold of emotions is a sufficient statistic for determining the emotional content of documents. While X, Y are high dimensional and discrete, Z is low dimensional and continuous.

2 Related Work

Studying emotions and their relations is one of the major goals of the psychology community. Important papers studying the low dimensional structure of emotions are [18, 16, 17, 19]. Under the context of document analysis, [12] survey progress in sentiment analysis over the recent decade.

Some recent work on mood classification are [4] that used linguistic features to detect emotions of internet chatting, and [14] that classified data using the model suggested by [18]. [8] used blog posts to classify moods with standard machine learning techniques, while [7] exploit a mood hierarchy to improve classification results.

[9] classified time stamped documents in order to show the changes in public moods over time. [11] used a similar approach to compare tweeter sentiment and gallop polls. [5] visualize the public moods found in Twitter across time.

3 The Statistical Model

Several studies in the psychology literature analyzed human survey data to conclude that human emotions have a low dimensional structure. The most striking factor conveys a concept similar to positive-negative sentiment. Another prominent factor is the engagement level, which includes on one end emotions such as quiet and still, and on the other end emotions such as aroused and surprised. While all possible combinations of these two factors lead to possible human emotions, some positive correlation exist. See [18, 17, 16] and Figure 1 for more information on these and additional psychological factors. These studies motivate our approach of modeling emotions or moods (we use the two terms interchangeably in this paper) on a low dimensional continuous space.

We denote the document, typically in a bag of words or n -gram representation as X , its mood or emotion content as multiclass label variable $Y \in \{1, \dots, C\}$, and the mood manifold coordinates (in the ambient space) as $Z \in \mathbb{R}^l$. Labeled training data typically consists of pairs $(x^{(i)}, y^{(i)})$ where $y^{(i)}$ is the mood that is expressed in the document $x^{(i)}$. In our case of crawled blog entries from `livejournal.com`, the authors annotated the entries with their emotions through a rich set of emoticons (see Section 4 for more information).

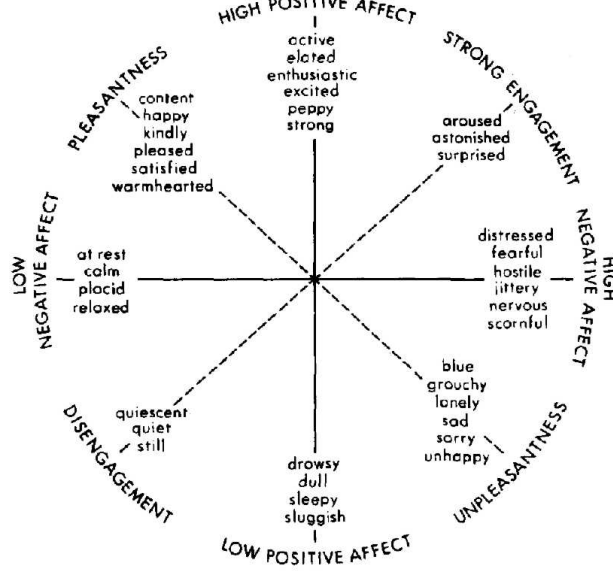


Figure 1: The two-dimensional structure of emotions from [18]. We can interpret top-left to bottom-right axis as expressing sentiment and the top-right to bottom-left axis as expressing engagement.

We make four modeling assumptions:

1. $X \rightarrow Z \rightarrow Y$
2. $\{Z|Y = y\} \sim N(\mu_y, \Sigma_y).$ (1)
3. $\{Z|X = x\} \sim N(\theta^\top x, \Sigma_x).$
4. The distances between the vectors in

$$\{E(Z|Y = y), y \in C\}$$

are similar to the corresponding distances in

$$\{E(X|Y = y), y \in C\}.$$

The first assumption is consistent with the psychological survey studies: the continuous mood representation Z is the internal emotion while the emotion label Y is simply a discretization of the continuous Z . The second assumption implies that the distribution over the manifold of emotions given a specific emotion is a multivariate Gaussian distribution. The third assumption implies a (multi-response) linear regression relationship between Z and X . The fourth assumption states that the spatial proximities of the mood centroids in the Z space is similar to the spatial proximities between the mood centroids in the bag of words or n -gram space.

The assumptions above may be modified if needed. For example, the Gaussian distribution for $Z|Y$ may be replaced with a mixture of Gaussians. The linear regression $X \rightarrow Z$ may be replaced with an alternative non-linear regression. We decided on the above model as it is intuitive and simple, it follows classical models, it leads to convenient computational schemes, and it works well in practice.

3.1 Fitting the Model Parameters and Applying it

Motivated by Assumption 4, the parameters $\mu_y = \mathbb{E}(Z|Y = y), y \in C$ are determined by running multi-dimensional scaling (MDS) or Kernel PCA on the empirical versions of $\{\mathbb{E}(X|Y = y), y \in C\}$ (replace expectation with train set average).

The parameter θ defining the regression $X \rightarrow Z$ is fitted by maximizing the conditional likelihood

$$\begin{aligned}\hat{\theta} &= \arg \max_{\theta} \sum_i \log p(y^{(i)}|x^{(i)}) \\ &= \arg \max_{\theta} \sum_i \log \int_Z p(y^{(i)}|z) p_{\theta}(z|x^{(i)}) dz \\ &= \arg \max_{\theta} \sum_i \log \int_Z p(z|y^{(i)}) \frac{p(y^{(i)}) p_{\theta}(z|x^{(i)})}{\sum_y p(z|y) p(y)} dz.\end{aligned}\tag{2}$$

The covariance matrices Σ_y of the Gaussians $Z|Y = y, y = 1, \dots, C$ may be estimated by computing the empirical variance of z values simulated from $p_{\hat{\theta}}(Z|X^{(i)})$, for all i such that $Y^{(i)} = y$. Alternatively, the samples may be replaced with the most likely values

$$\left\{ \arg \max_z p_{\hat{\theta}}(Z|X^{(i)}) : i = 1, \dots, n \right\}.$$

Given a new test document x , we can predict the most likely emotion with

$$\begin{aligned}\hat{y} &= \arg \max_y \int p(y, z|x) dz \\ &= \arg \max_y \int p(y|z) p_{\hat{\theta}}(z|x) dz.\end{aligned}\tag{3}$$

But in many cases, the distribution $p(Z|X)$ provides more insightful information than the single most likely emotion.

3.2 Approximating High Dimensional Integrals

Some of the equations in the previous section require integrating over $Z \in \mathbb{R}^l$, a computationally difficult task when l is not very low. There are, however, several ways to approximate these integrals in a computationally efficient way.

The most well-known approximation is probably Markov chain Monte Carlo (MCMC). Another alternative is the Laplace approximation. A third alternative is based on approximating the Gaussian pdf with Dirac's delta function, also known as an impulse function, resulting in the approximation

$$\begin{aligned}\int N(z; \mu, \Sigma) g(z) dz &\approx c(\Sigma) \int \delta(z - \mu) g(z) dz \\ &= c(\Sigma) g(\mu).\end{aligned}\tag{4}$$

A similar approximation can also be derived using Laplace's method. Obviously, the approximation quality increases as the variance decreases.

Applying (4) to (2) we get

$$\begin{aligned}\hat{\theta} &\approx \arg \max_{\theta} \sum_i \log \frac{p(y^{(i)})p_{\theta}(z^{(i)*}|x^{(i)})}{\sum_y p(z^{(i)*}|y)p(y)} \\ &= \arg \max_{\theta} \sum_i \log p_{\theta}(z^{(i)*}|x^{(i)})\end{aligned}\tag{5}$$

where

$$z^{(i)*} = \arg \max_z p(z|y^{(i)}) = E(Z|y^{(i)}),$$

which is equivalent to a least squares regression.

Applying (4) to (3) yields a classification rule

$$\hat{y} \approx \arg \max_y p\left(y \middle| Z = \arg \max_z p_{\hat{\theta}}(z|x)\right).\tag{6}$$

4 Applications and Experiments

In this section, we examine some applications of our model and report experimental results.

4.1 Datasets

We used crawled Livejournal¹ data to fit the model parameters. Livejournal is a popular blog service that offers emotion annotation capabilities to the authors. About 20% of the blog posts feature these optional annotations in the form of emoticons. The annotations may be chosen from a pre-defined list of possible emotions, or a novel emotion specified by the author. We crawled 465,945 documents featuring the most popular 100 emotions. Two other datasets that we use in our experiments are movie review data [13] and restaurant review data² [2].

We used Indri from the Lemur project³ to extract term frequency features from these three datasets while tokenizing and stemming words. As is common in sentiment studies [1, 10, 6] we added new features representing negated words. For example, the phrase “not good” is represented as a token “not-good” rather than as two separate words. This resulted in 31,726 features.

4.2 Exploring Mood Manifold

Figure 2 shows the locations of $E(Z|Y = y)$ for the most popular 31 moods, in the first two dimensions of the mood manifold. The choice of two dimensions was done for visualization purposes. In later sections we indeed consider higher dimensional ambient spaces for the manifold of emotions.

We make the following observations.

1. The horizontal axis expresses a sentiment-like emotion. The left part features emotions such as *happy* and *cheerful*, while the right part features emotions such as *sad* and *depressed*. This is in agreement with Watson’s observations (see Figure 1) that identify positive-negative sentiment as the most prominent factor among human emotions.

¹<http://www.livejournal.com>

²<http://www.cs.cmu.edu/~mehr/bod/RR/>

³<http://www.lemurproject.org/>

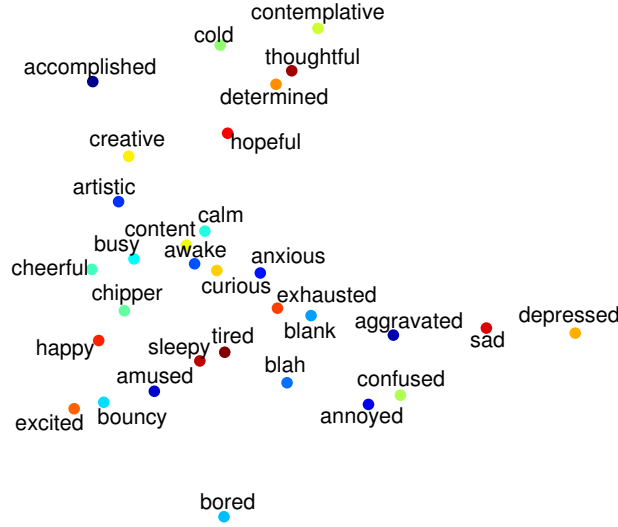


Figure 2: Mood Centroids $E(Z|Y = y)$ on the two most prominent dimensions in emotion space fitted from blog posts. The horizontal dimension corresponds to negative vs. positive sentiments and the vertical dimension corresponds to engagement level (compare with Figure 1).

2. The vertical axis expresses the level of engagement. The top part features emotions such as *thoughtful* or *contemplative*, while the bottom part features emotions such as *bored*. This also agrees with Watson’s psychological model.
3. The right part is spatially focused while the left part is dispersed. In other words, we have a clear one dimensional curve starting on the right, and as it moves to the left it spreads out to fill the space. We conclude that there is higher diversity among positive emotions than among negative emotions.

Another way to analyze the model is by examining which words receive high weights for the different axes. The words with highest weight associated with the horizontal axis are indeed sentiment words: {*depress*, *sad*, *confuse*, *depression*, *cry*, *rip*, *sigh*, *upset*, *died*, *not-understand*} on the negative side and {*excite*, *yay*, *awesome*, *not-wait*, *happy*, *welcome*, *laugh*, *glad*, *lol*, *amaze*, *proud*, *haha*} on the positive side.

We conclude that there are agreements between our model and standard psychological models. The sentiment concept emerges as the top factor in both models. The second most prominent factor, the engagement level, is also a close match. It is remarkable that the same structure of emotions arise from two different data sources: human surveys and annotated blog posts. Our framework may contribute several additional markers to psychological models [18, 19]: *bored* as negative engagement marker, and *thoughtful*, *contemplative* as positive engagement markers.

4.3 Emotions on the Manifold

The emotion space represented by Z is stochastically related on the emotion label Y . This relation $P(Z|Y)$ may also be used to examine the relationship between different emotions. The examination should be consistent to some extent with our understanding of emotion, though some discrepancies may reveal interesting insights.

Since two emotions are represented by Gaussian distributions on Z , a natural distance measure between two emotions is the Hellinger distance between the corresponding densities

$$d^2(f, g) = \int \left(\sqrt{f(z)} - \sqrt{g(z)} \right)^2 dz. \quad (7)$$

Since each density integrates to one, (7) is equivalent to the Bhattacharyya coefficient

$$B(f, g) = -\log \int \sqrt{f(z)g(z)} dz,$$

which has the following closed form in the case of two multivariate Gaussians

$$B(N(\mu_1, \Sigma_1), N(\mu_2, \Sigma_2)) = \frac{1}{8}(\mu_1 - \mu_2)^T \left(\frac{\Sigma_1 + \Sigma_2}{2} \right)^{-1} (\mu_1 - \mu_2) + \frac{1}{2} \log \left(\frac{\det((\Sigma_1 + \Sigma_2)/2)}{\sqrt{\det \Sigma_1 \det \Sigma_2}} \right).$$

Following common practice, we add a small value to the diagonal of the covariance matrices to ensure invertibility.

Figure 3 shows the mood dendrogram obtained by hierarchical clustering the top 31 emotions using the Bhattacharyya coefficient (complete linkage clustering). The bottom part of dendrogram was omitted due to lack of space. The clustering is in agreement with our intuition. For example,

1. aggravated and annoyed are in the same tight cluster and close to confused,
2. sad and depressed are in the same tight cluster,
3. bouncy, cheerful, and happy are in the same tight cluster, which is close to accomplished and excited, and
4. bored, sleepy, and tired are in the same tight cluster.

The hierarchical clustering is useful in many ways. When the original emotions hierarchy is too fine (there are over 100 emotions in our data) we may choose to aggregate similar emotions into “super emotions”. If our particular situation requires paying attention to one or two “types” of emotions we can use particular mood cluster to reflect the desired feature. For example, when analyzing product reviews we may want to partition the emotions into two clusters: positive and negative. When analyzing the effect of a new advertisement campaign we may be interested in a clustering based on engagement: excited and energetic vs. bored. Other situations may call for other clusters of emotions.

Figure 2 shows the spatial arrangements of $E(Z|Y = y)$ in the Z space. A more careful analysis should also take into consideration the covariance matrices of $P(Z|Y = y)$, rather than just the expectation vectors. Figure 4 shows the Voronoi tessellation corresponding to

$$f(z) = \arg \max_{y=1, \dots, C} p(Z|Y = y)$$

For space and clarity purposes we use 15 “super-emotions” obtained by clustering the original set of emotions as described above, instead of the entire set of 31 or 100 top emotions.

We observe that:

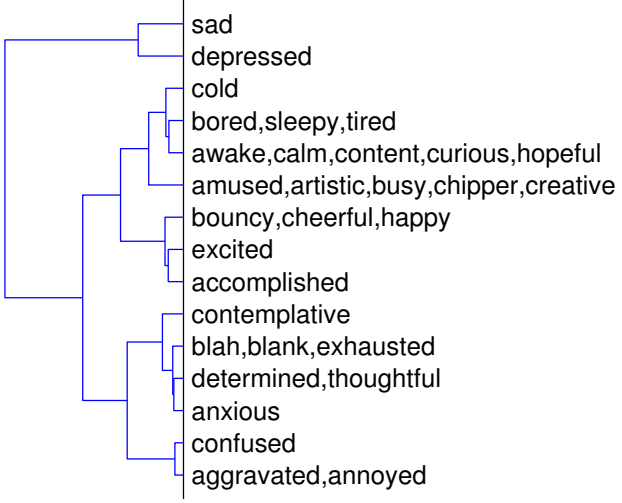


Figure 3: Dendrogram of moods using complete linkage function on Bhattacharyya distances between moods. The leaves are cut in 15 clusters to reduce clutters.

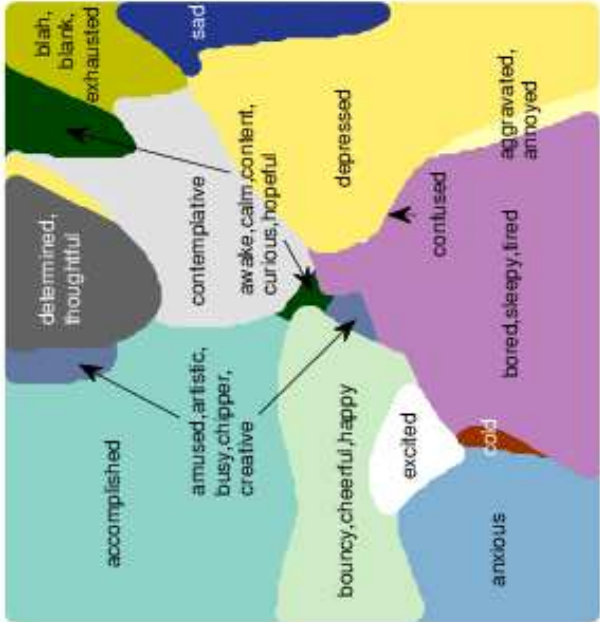


Figure 4: Voronoi tessellation of the space spanned by the first two dimensions of mood manifold with 15 "super-emotion" clusters, based on the $\arg \max_y p(Z|Y = t)$ function.

1. As in Figure 2 the horizontal axis corresponds to positive-negative emotion and the vertical axis corresponds to engagement: thoughtful and contemplative vs. bored and tired.
2. The depressed region is spread significantly on the bottom-right side, and is neighboring the bored, sleepy, tired region and the sad region.
3. The region corresponding to the bouncy, cheerful, happy emotions neighbors the accomplished region and the excited region.

A similar tessellation of a higher dimensional Z space should provide a finer relationships between human emotions.

4.4 Classifying Emotions

An important application, analogous to sentiment analysis, is emotion classification. In other words, given a document x predict the emotion that is expressed in the text.

As mentioned in the introduction, it is possible to do that by constructing separate $p(y_i|x)$ models for every emotion (one-vs-all approach). The one vs. all approach is not entirely satisfactory as it ignores the relationships between similar and contradictory moods. Why should we not use documents labeled as `sleepy` when we fit a model for predicting `tired`. On the other hand, it is not clear how to count these documents since `sleepy` and `tired` are not identical emotions.

Our framework accounts for the relationship between similar and contradictory emotions automatically as it assumes a hidden continuous representation, where $P(Z|Y = y)$ reflects a non-trivial relationship between the emotions. Our earlier attempts to construct a manual relationship between emotions based on domain knowledge did not perform well. Our current approach is data driven and indeed it outperforms the one vs. all approach, as we show below. Our one vs. all baseline is a regularized logistic regression, operating in the original bag of words feature space — one of the strongest text classification baselines.

Since $P(Z|Y = y)$ are Gaussian, the resulting Bayes classifier, which minimizes the classification risk, is the well known quadratic discriminant analysis (assuming $\text{Var}(Z|Y = y)$ depends on y), or the well-known linear discriminant analysis (assuming that $\text{Var}(Z|Y = y)$ does not depend on y).

We considered three different models for the covariance matrices: full covariance, diagonal covariance, and linear combination of full covariance and spherical covariance:

$$\hat{\Sigma}' = (1 - \lambda)\hat{\Sigma} + \lambda \left(\sum_{i=1}^C \hat{\Sigma}_{ii} \right) I \quad (\text{LDA})$$

$$\hat{\Sigma}'_y = (1 - \lambda)\hat{\Sigma}_y + \lambda \left(\sum_{i=1}^C [\hat{\Sigma}_y]_{ii} \right) I \quad (\text{QDA}).$$

In either case we used a C dimensional ambient space (C equals the number of emotions) and the approximation (6).

Classification experiments (Figure 5–6) are performed on the Livejournal data with the most popular 32 moods, 100 moods, and the 15 clusters from Figure 3. Half of the data is used for the training and the other half for testing. t -tests are performed on 10 random trials to determine statistical significance. Low accuracies are expected in this task because there are many similar emotions that significantly overlap each other. We also designed three sample binary classification tasks obtained by partitioning the set of moods into two clusters (positive vs. negative sentiment, engagement vs. boredom, and anger vs. calm).

Method	F1	Acc.	Method	F1	Acc.	Method	F1	Acc.
logistic reg.	0.7282	0.8108	logistic reg.	0.6015	0.7892	logistic reg.	0.6352	0.8459
LDA diag.	0.7332	0.7872	LDA diag.	0.6662	0.7690	LDA diag.	0.7374	0.8555
LDA full	0.7352	0.8141	LDA full	0.6395	0.7903	LDA full	0.7092	0.8597
QDA diag.	0.7290	0.7979	QDA diag.	0.6598	0.7268	QDA diag.	0.7315	0.8546
QDA full	0.7266	0.8108	QDA full	0.6714	0.7733	QDA full	0.7221	0.8601

Figure 5: F1 and accuracy over test-set in sentiment task (left): {cheerful, happy, amused} vs {sad, annoyed, exhausted}, in detecting engagement level (middle) {tired, bored, sleepy} vs {determined, thoughtful}, and in detecting anger (right) {annoyed, aggravated} vs. {calm, content}. Bold text represent statistically significant (t -test) improvements over the regularized one vs. all logistic regression baseline in the original feature space.

Method	Macro F1	Acc.	Method	Macro F1	Acc.	Method	Macro F1	Acc.
logistic reg.	0.1357	0.1657	logistic reg.	0.0441	0.1116	logistic reg.	0.1895	0.2566
LDA diag.	0.1363	0.1666	LDA diag.	0.0545	0.1100	LDA diag.	0.2112	0.2480
LDA full	0.1474	0.1691	LDA full	0.0627	0.1130	LDA full	0.2209	0.2571
QDA diag.	0.1380	0.1587	QDA diag.	0.0543	0.1032	QDA diag.	0.2068	0.2509
QDA full	0.1494	0.1593	QDA full	0.0539	0.0929	QDA full	0.2134	0.2577

Figure 6: Macro F1 score and accuracy over the test set in multiclass emotion classification. Left panel shows classification over top 32 moods. Middle panel shows classification of top 100 moods. Right panel shows classification of the 15 clusters from Figure 3. Bold text represent statistically significant (t -test) improvement over the regularized one vs. all logistic regression in the original feature space.

Figure 5 and Figure 6 compare classification results using the emotion manifold model (LDA/QDA with different covariance matrix models) and a regularized logistic regression baseline on the original bag of words feature. Most of the experimental results show that the emotion manifold model results in a statistically significant classification improvement. The improvements are especially noticeable in the F1-measures; it can be seen that mood categories with less training data benefit more from since these minor classes contribute more on macro f1 than accuracy measure.

4.5 Sentiments and the Emotion Manifold

The concept of positive-negative sentiment fits naturally within our framework as it is the first factor in the continuous Z space. Nevertheless, it is unlikely that all sentiment analysis concepts will align perfectly with this dimension. Indeed, it is likely that different sentiment concepts, for example movie reviews and restaurant reviews do not represent identical concepts.

We model a sentiment concept as a smooth one dimensional curve within the continuous Z space. As we traverse the curve, we encounter documents corresponding to negative sentiments, changing smoothly into emotions corresponding to positive sentiments. We complement the stochastic embedding $p(Z|X)$ with a smooth probabilistic mapping $\pi(R|Z)$ into the sentiment scale. The prediction rule becomes

$$\hat{r} = \arg \max_r \int p(Z = z|X) \pi(R = r|Z = z) dz$$

and its approximated version is

$$\hat{r} = \arg \max_r \pi \left(R = r \middle| Z = \arg \max_z P(Z = z|X) \right) dz.$$

Figure 7 (top) shows the smooth curves corresponding to $E[\pi(R = r|Z)]$ for movie reviews and restaurant reviews. Both curves progress from the right (low sentiment) to the left (high sentiment). But the two curves show a clear distinction: the movie review sentiment concept is in the top part while the restaurant review sentiment concept is in the bottom part. Obviously, the two sentiment concepts are different: movie reviews are evidently more thoughtful and creative than restaurant reviews.

Figure 7 (bottom left and right) show the test L_1 prediction error of our method and a baseline (regularized linear regression trained on the original bag of words features) as a function of the train set size. The manifold regression performs better than regression on the original bag of words features when the train set is small. As the train set increases, the regression on the full bag of words features outperforms the manifold model (for $n = 4000$, the L_1 difference between the two models for movie reviews on 1-10 scale is 0.198).

We make the following observations.

1. Sentiment concepts in different contexts are not interchangeable. They correspond to different curves in the manifold of emotions, as is nicely demonstrated by Figure 7 (top).
2. The model parameters defining $X \rightarrow Z \rightarrow Y$ are fitted using blogs entries labeled with author emotions. The regression model $\pi(R|Z)$ is fitted using a separate sentiment training data. Since Z is lower dimensional than the original bag of words, we can expect our approach to be more accurate when the labeled sentiment data is scarce. For the same reason, it is more feasible to train a complex non-linear model on the manifold of emotions, than on the bag of words representation.
3. Concepts such as movie or restaurant ratings are not solely captured by manifold of emotions. This is not surprising as many review sentences make non-emotional high-level arguments that are not

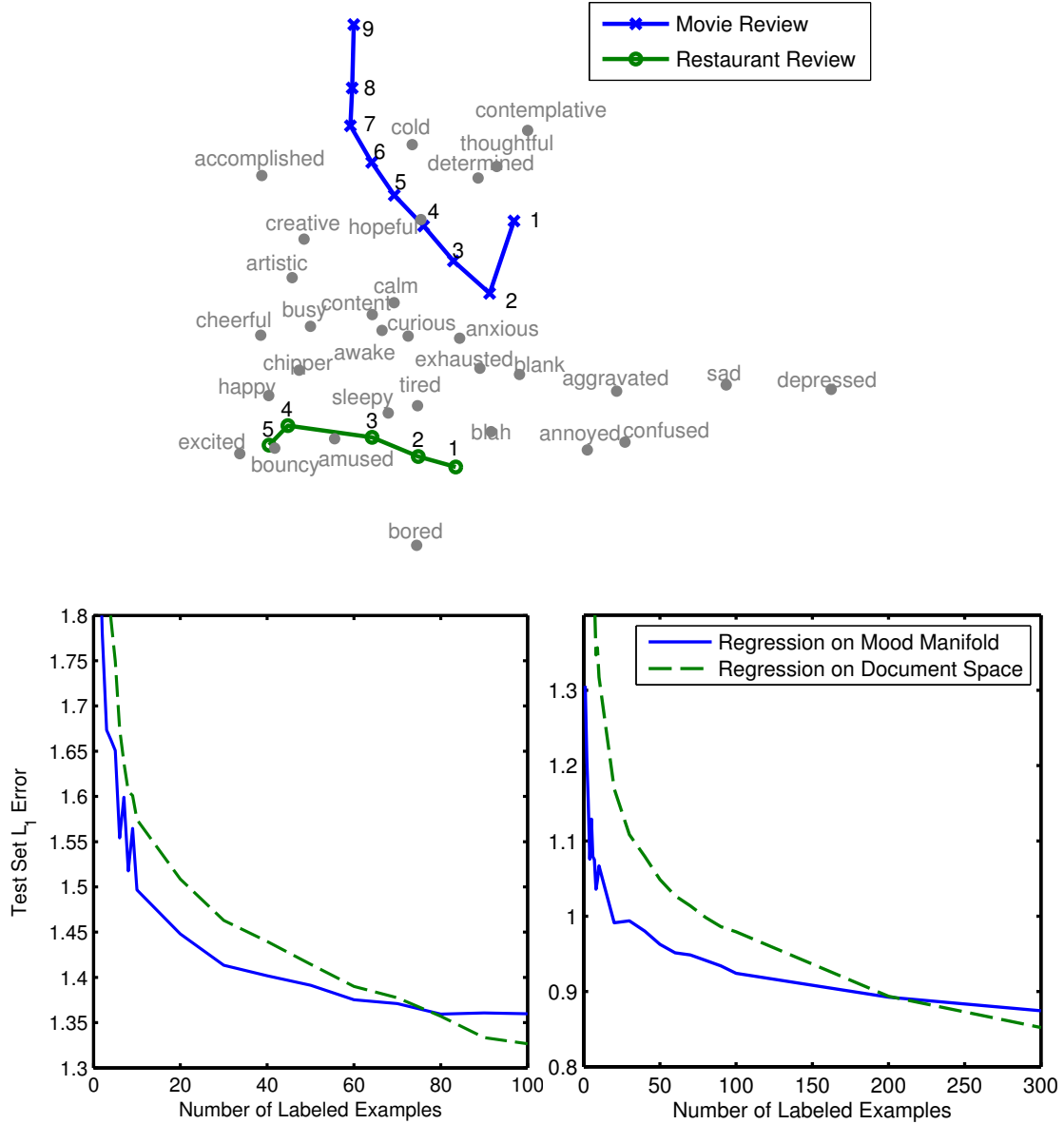


Figure 7: Top: Projected centroids of each review score (higher is better) of movie reviews and restaurant reviews on the mood manifold. Both review start from the right side (negative sentiment in mood manifold) and continues to the left side (positive sentiment) with two different unique patterns. Movie reviews are evidently more thoughtful and creative than restaurant reviews. Bottom left and right: L_1 test prediction error on movie review (left) and restaurant review (right) as a function of the sentiment train set size. Prediction using the manifold of emotions outperforms the baseline (linear regression) for smaller training set sizes.

captured by the continuous Z space. Consider for example, the following sentence, taken from a positive review: “*Crumb* is a rare and powerful documentary that completely absorbs the viewer and leaves an impression so blindingly clear that the afterimage cannot be blinked away even when the theater is far behind.” This explains the improved performance of the linear regression baseline (using the original bag of words features) when there is sufficient training data.

5 Discussion

In this paper, we introduced a continuous representation for human emotions Z and constructed a statistical model connecting it to documents X and to a discrete set of emotions Y . Our fitted model bears close similarities to models developed within the psychological literature, based on human survey data.

Among the many applications of our model are: discovering the complex relationships between emotions, clustering of emotions, improved classification of emotions, and sentiment prediction.

Several attempts were recently made at inferring insights from social media or news data through sentiment prediction. Examples include tracking public opinion [11], estimating political sentiment [15], and correlating sentiment with the stock market [3]. It is likely that a more comprehensive and multivariate view of emotions will help make progress on these important and challenging tasks.

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